Knowledge is power: electric vehicle calculator for cold climates

Michelle M. Wilber, corresponding author - mmwilber@alaska.edu[a]
Jennifer I. Schmidt[b]

[a] Alaska Center for Energy and Power, University of Alaska Fairbanks, PO Box 755910 Fairbanks, Alaska 99775, USA
[B] Institute of Social and Economic Research, University of Alaska Anchorage, 3211 Providence Dr., Anchorage, AK 99508, USA

Abstract
We used crowdsourced data in Alaska and the literature to develop a light-duty electric vehicle model to help policymakers, researchers, and consumers understand the trade-offs between internal combustion and electric vehicles. This model forms the engine of a calculator, which was developed in partnership with residents from three partner Alaskan communities. This calculator uses a typical hourly temperature profile for any chosen community in Alaska along with a relationship of energy use vs. temperature while driving or while parked to determine the annual cost and emissions for an electric vehicle. Other user inputs include miles driven per day, electricity rate, and whether the vehicle is parked in a heated space. A database of community power plant emissions per unit of electricity is used to determine emissions based on electricity consumption. This tool was updated according to community input on ease of use, relevance, and usefulness. It could easily be adapted to other regions of the world. The incorporation of climate, social, and economic inputs allow us to holistically capture real world situations and adjust as the physical and social environment changes.

Keywords

Electric Vehicle, Alaska, Cold Climate, Parked Energy, Calculator, Energy Use

Funding: This work was supported by the National Science Foundation [grant numbers 2127171, 2127172]; the Office of Naval Research [grant number N00014-18-S-B001], and the Alaska Energy Authority.

1. Introduction
The widespread adoption of electric vehicles (EVs) has gained significant momentum in recent years due to their potential to reduce greenhouse gas emissions and dependence on fossil fuels in the transportation sector. Alaska's characteristics, such as its vast land area, cold climate, and distinct power generation mix, present particular challenges and opportunities in this transition.

Cold weather lowers EV efficiency and range, increases energy use, slows charging, and can decrease reliability and damage EV batteries [1,2]. However, a survey of the literature shows limited data on range and electrical efficiency below -20°C, with no data found below -30°C [3]. Alaska and other parts of the far north can be expected to have efficiency decreases and other impacts to EV use that differ markedly to those seen in the northernmost parts of the contiguous U.S., southern Canada, and most of Europe [4], but the data gathered in these cold climates can help inform winter performance in more temperate regions. Higher energy use due to cold weather leads to higher emissions and higher costs of ownership. Even the much smaller regional differences seen within the contiguous U.S. are considered large enough to affect adoption patterns and energy use with environmental implications [5].

Compounding the challenges, infrastructure in many Alaska communities is fundamentally different from those in most of Europe, China, the contiguous United States (U.S.), and other places with high EV uptake. Many of these communities are small and islanded in nature. Electrical grids lack transmission infrastructure, and are often powered by diesel fuel burned in smaller generators [6]. The largest connected grid in Alaska can still be considered a small collection of nested microgrids - although it connects regional utilities along the rail and major road system in Alaska, it is unconnected to any continental grid. Drivers on the connected road system of Alaska may have driving patterns more similar to those in other regions of the U.S. However, the many islanded communities in Alaska have very limited road systems of only a few miles (if any) that are unconnected to each other, contributing to very different vehicle use patterns. Averaged together, Alaska drivers tie for the lowest number of miles [7]. Because of the energy used by EVs to maintain a desired battery temperature [8], the parked energy use can be large compared to the driving energy use of low mileage vehicles in extreme climates, significantly raising the effective energy use per mile calculated from the total vehicle energy use, as shown in Section 2.3.

To effectively assess the feasibility and benefits of EV adoption in this region, it is crucial to develop specialized tools and models that account for the specific conditions and characteristics of the Alaska transportation landscape. Publicly available calculators look at state or national averages and do not adequately encompass the range of climates, power mixes, and use cases of Alaska [9,10,11]. None explicitly account for parked energy use of vehicles, and most do not adjust efficiency in response to temperature. This paper introduces an innovative EV charging cost and emissions calculator specifically tailored to the Alaska context [12]. Energy use data collected from EVs in the areas of Alaska shown in Figure 1 is used to create a model of EV energy use in extremely cold climates which is incorporated in the engine of the calculator [13]. The calculator aims to provide policymakers, researchers, and consumers with a comprehensive analysis of the costs and environmental impacts associated with operating EVs in Alaska. By incorporating various parameters, such as electricity rates, driving patterns, and local emissions factors, it enables accurate estimation and comparison of charging cost and emissions between different EV models and traditional internal combustion engine (ICE) vehicles. To develop the calculator, a multidisciplinary approach was adopted, encompassing expertise in energy modeling, energy economics, and social science. Development of the public calculator was a co-production with community members in Alaska who brought expertise in local vehicle use and insight into features that would add to the calculator’s relevance and ease of use.

The contributions of this paper extend beyond the development of the calculator itself. The calculator serves as a crucial tool for policymakers and utility managers. It can help them make informed decisions regarding EV infrastructure development, electricity grid planning, and emission reduction strategies. Additionally, it assists researchers in evaluating the environmental benefits of EV adoption in Alaska and provides consumers with valuable insights into the economic viability of EV ownership. This calculator can easily be modified for use in other regions through the addition of regional databases and models of EV energy use in warm climates where significant cooling is needed.

The remainder of this paper is organized as follows: Section 2.1 presents the Alaska data and the derivation of the underlying energy use model used in the calculator. Section 2.2 describes the methodology and data sources utilized in the development of the EV calculator. Section 2.3 presents verification obtained from applying the calculator to two Alaska vehicles whose data were not used in the development of the energy use model. Finally, Section 3 concludes the paper, emphasizing the significance of the calculator in supporting sustainable transportation planning and highlighting avenues for future research and improvement.

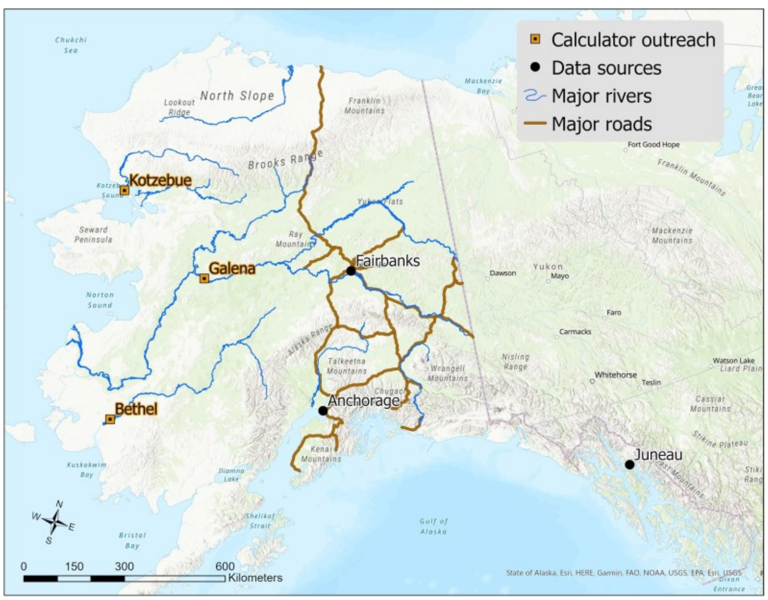

Figure 1. Map of Alaska showing locations of EVs providing data for this analysis and communities providing feedback on the calculator.

2. Materials and Methods

2.1. EV Energy Use

Although statistical modeling from data collected in repeated and controlled experiments is the gold standard, the expense of expanding a dataset this way across vehicle models is prohibitive. Therefore, crowdsourcing of EV data from owners in the state was used to expand the knowledge on energy use. The energy use of EVs was evaluated as a function of temperature and use case. Use cases were broken into driving and parked energy, with the parked state further broken into: ‘parked while unplugged’, ‘parked while plugged in’, and ‘warm idle’. Vehicles are commonly plugged into an electrical outlet to help maintain battery temperature during winter months (see section 2.1.2 for more details). Even though there are many other settings that could be included, these categories capture the major drivers of efficiency, avoid overwhelming users, and are sufficient to create a working model given the limitations of the data available.

2.1.1. Driving Energy Use

The methodology and analysis results for modeling EV energy use vs. temperature for passenger vehicles while driving is given in Wilber et al, 2022 [14]. Although energy use will depend on a number of factors such as trip length, route grade, vehicle settings, driver behaviors, etc. [15, 16, 17, 18, 19, 20, 21], it is highly temperature dependent [22, 23, 24] due to the energy use of the cabin and battery conditioning systems that maintain desired temperature setpoints. Data on the relationship of energy use with temperature for passenger EVs in the literature [25, 26, 27, 28, 29] were combined with crowdsourced data from EVs in Alaska. There is a strong positive linear relationship between energy use and temperature between -40°C to about 20°C in Alaska. However, additional data from warmer climates, where significant cooling is needed, results in a third order polynomial providing the best fit. The relationship for passenger EVs found in this study is reproduced in Equation 1 below:

$$RE(T) = E(T)/E = 0.000011\, T^3 + 0.00045\, T^2 - 0.038\, T + 1.57 \qquad \text{EQN 1}$$

Where:
T is ambient temperature in °C
$RE(T)$ is relative energy use per unit distance traveled at temperature T
$E(T)$ is the energy use per unit distance traveled at temperature T
E is the minimum energy use per unit distance traveled

The EVs used to define Equation 1 were all passenger vehicles with a rated energy use in the narrow range of 0.27 to 0.34 kWh per mile (kWh/mi) [30]. The minimum energy use per unit distance traveled, E, is less than this rated value by a factor of approximately 1.15 [29]. With the analysis of further light duty EV data, it became apparent that EVs with different rated energy uses have temperature dependent energy uses that have a similar slope at temperatures that require heating (below about 20°C) but were offset from each other by a ratio of the rated energy use. Therefore, Equation 1 was modified into Equation 2 to better fit the light duty EVs studied to data by using an E of 0.24 kWh/mi (0.28 kWh/mi divided by 1.15) to solve for the coefficients of the higher order terms. Datasets from seven Teslas in Alaska that were not used in the original analysis are presented in Figure 2 and illustrate the effectiveness of Equation 2 for passenger EVs with varying rated energy uses.

$$E(T) = 0.0000027\, T^3 + 0.00011\, T^2 - 0.0093\, T + 1.37\, epm \qquad \text{EQN 2}$$

Where *epm* is the EPA rated energy use per mile in kWh/mi [30].

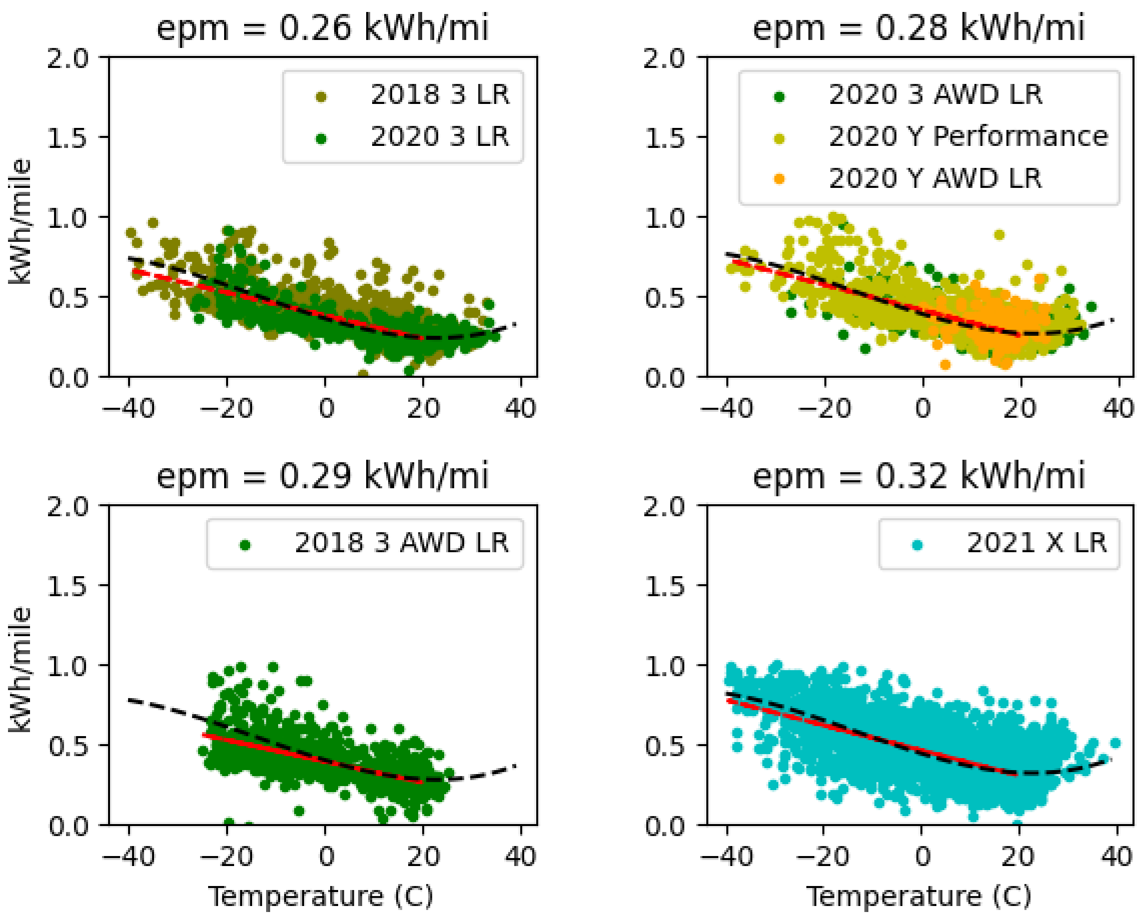

Figure 2 - Data from seven Teslas in Alaska with varying EPA rated energy use per mile (epm) showing a linear fit to the data points from each subplot in the heating regime (below 20°C) in red, and the model, using Eqn. 2, in black. The legend gives the color-coded individual Tesla models included in each subplot. Equation 2 was developed using national data for thousands of EVs as well as data from seven Alaska EVs including Chevy Bolts and various Tesla Models, not including the data presented in this figure.

Figure 3 compares the relationship in Equation 2 with published national data. Despite the much larger number of vehicles represented in this dataset, there is very limited data below -20°C, and none below -30°C, therefore some averages from the Alaskan data at the coldest temperatures are also shown in Figure 3. It can be seen that average vehicle speed and driving conditions (urban or highway) play a big role in energy consumption, especially at lower temperatures [31]. Other factors in the real-world driving data, such as driver aggressiveness, road conditions, length of trip, and whether vehicles start trips warm or cold soaked also undoubtedly contribute to the large scatter in the data. A general calculator must average over many of these real world factors for ease of use, and for this purpose the relationship in

Equation 2 seems to represent a reasonable fit to the entire dataset. Datasets that report only range reduction with temperature are recast as energy use per distance (kWh/mi) assuming that this value increases inversely proportionally to range reduction. The EV WATTS and Bolt data used in Figure 3 do not contain any trip level information that would allow a speed determination to be made. These data plot at the low end for energy use per unit distance for the temperature, which could be due to a high proportion of high speed/highway trips in the data or some other factor.

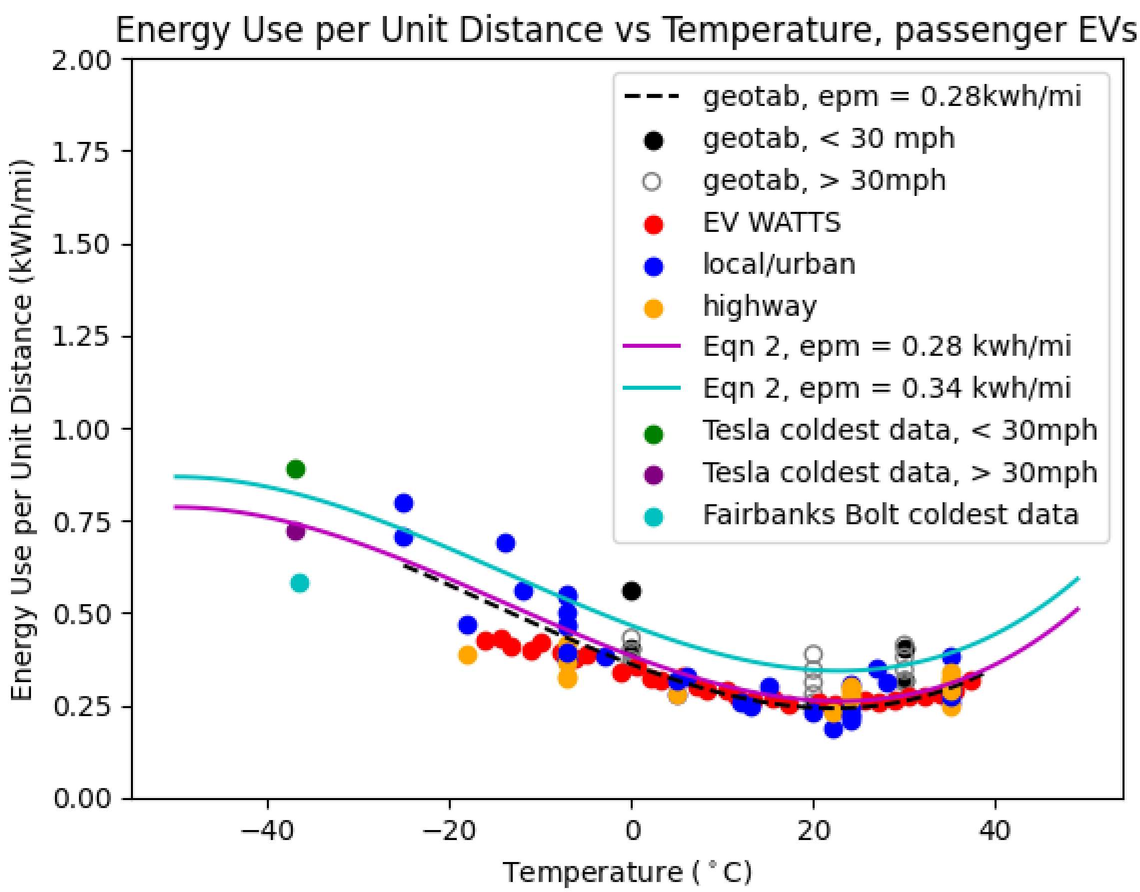

Figure 3 - Comparison of our model (Eqn. 2) to the published national data for passenger EVs. A published Geotab [29] average range reduction with temperature curve (black dashed line) recast as kwh/mi assuming an EPA rated energy use per mile (epm) of 0.28 kwh/mi. Geotab has also published range curves for different speeds at three different temperatures [31], and those are here recast to kwh/mi and binned to speeds less than 30 mph (black dots) and those greater than 30 mph (gray dots). The Geotab dataset includes anonymized data from over five million trips taken by 4,200 EVs including 102 different EV makes, models and years. Energy use per distance from a report on national statistics from the EV WATTS DOE National Lab dataset for over 400 battery electric vehicles [32] is plotted in red, it is noted that data is limited at high and low temperatures and only 36 non-hybrid EVs in the dataset reach temperatures of -20°C. Three other published data sets [25,26,27] encompassing nine EVs of different makes, models and years tested in controlled conditions are plotted with local/urban (blue dots) and

highway conditions (orange dots). Three averages from the Alaska dataset are also plotted: in green is the average of all the Fairbanks Tesla data (which includes three vehicles) between -40 and -30°C where average trip speed was less than 30 mph, in purple is the average for the same data where the average trip speed was greater than 30 mph. In cyan is the average of a single Fairbanks Bolt's data between -40 and -30°C. Eqn. 2 is plotted using the upper-end epm seen in the data of 0.34 kWh/mi (upper cyan curve) and the more typical 0.28 kWh/mi (lower magenta curve).

Limited data is available currently on the energy use of electric pickup trucks and full-sized SUVs since these are only recently available on the market. Others have used relative cabin size and rated efficiencies to extrapolate from electric sedan data to trucks [33], but for this study cold weather study we use data from two Ford F150 Lighting electric pickups operated by ConocoPhillips on the the North Slope of Alaska to estimate energy use by trucks (Figure 4). Using Equation 2 with a rated kWh/mi of 0.50 kWh/mi for the Ford Lightning [30] gives a good approximation of the best linear fit of the data.

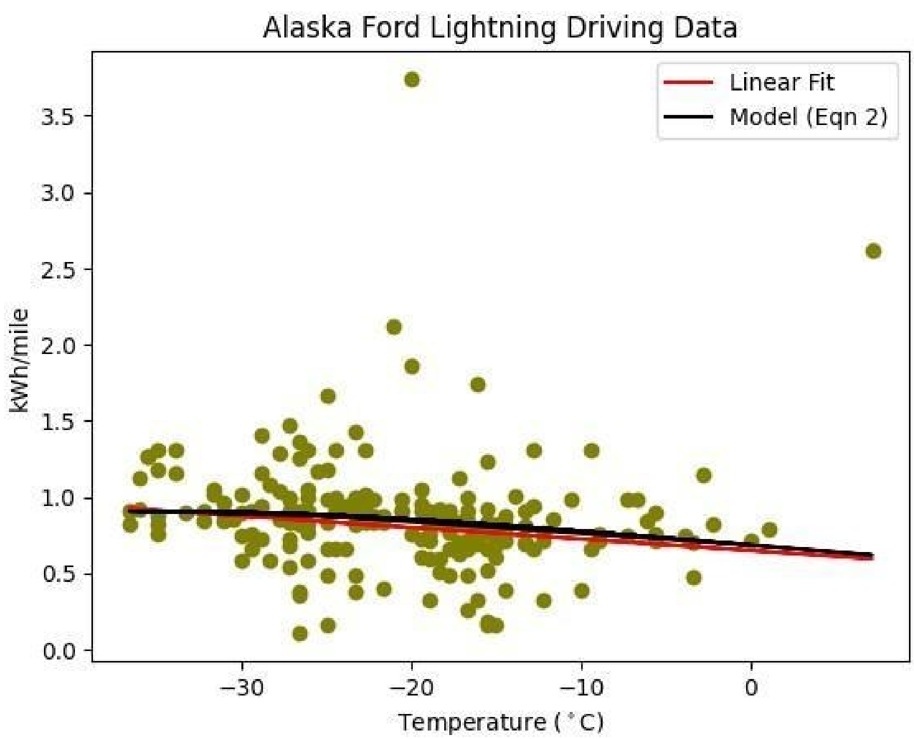

Figure 4: Data from two Alaskan electric light duty trucks showing a linear fit to the data points in red, and the model, using Eqn. 2, in black.

2.1.2 Parked Energy Use:

EVs use energy when parked for many things - sending and receiving data, engaging security cameras, and also keeping the battery at a desired temperature. The energy used while an EV is parked can be significant and must be accounted for in an accurate assessment of the total energy used by the vehicle. ICE vehicles may also use some energy from the battery for similar uses, but this is generally very small due to the small size of the starter battery. In cold climates, block heaters, oil pan heaters, battery blankets and other devices may be plugged into outlets to provide additional energy to the ICE vehicle to maintain reliability and life in cold temperatures, but these energy uses are generally after-market and under the control of the user. The EVs parked energy use is based on the Battery Thermal Management System and other settings, and is not generally controllable by the user. Self discharge is expected to be a negligible part of the energy loss while a vehicle is parked, in the range 1 to 5% per month, or about 0.001 kWh/hr for a typical EV battery pack [34].

Based on suggestions from owners and online forums that battery heater settings and energy use was different in the plugged and unplugged case, the parked energy data was analyzed for three different cases: (1) parked and plugged into an active charging station, (2) parked and unplugged, and (3) warm idle - parked, but using energy to heat or keep the cabin warm. Warm idle is an important state of a vehicle, used by many in cold weather to maintain comfort for people or pets waiting in the car, or to ensure it when occupants return to the car after an errand (and used in extremely cold temperatures to make sure the car does not fail to start again due to the cold). We use the term 'idle' euphemistically in the case of EVs as there is no engine left idling, just energy used from the battery or from the charging equipment to keep the vehicle warm.

Analyzing crowdsourced data for parked energy use is more challenging than doing so for energy use per mile while driving. Telematic vehicle data collected by apps generally only collects data when the vehicle is on (driving, idling, or charging) and often is presented at the trip or charging session level, not broken out for parking or idling only. Hand collected data is commonly reported as trip beginning and ending odometer readings and charging session energy consumption, again making a breakout of parked energy use challenging. A few vehicles in our study were used to assess parked energy use as follows, data is shown in Figure 5:

<u>Bolt, plugged in data:</u> Data was provided for three 2017 Chevrolet Bolts. The Bolt is left on the charger until fully charged to the set-point of the vehicle, then the charging session is restarted and the total kWh used during a period of hours is recorded, along with the total time plugged in. Energy use in kWh is either reported by a ChargePoint [35] smart charger or by a separate metering device (a Killawatt meter with a stated 0.2% accuracy [36] that a level-1 charger is plugged in to or a current transformer-based Emporia Vue 2 meter, 2% accuracy, [37] attached to the charger circuit.) In this and the subsequent cases, temperature data is recorded from a local weather station [38, 39] and averaged over the duration of the test.

<u>Bolt, unplugged data:</u> Data was gathered for a single 2017 Chevrolet Bolt using the Emporia Vue 2 meter. The Bolt is left on the charger until fully charged to the vehicle set-point, then unplugged for a period of hours, before being plugged back in and the energy to charge back to the full set point is recorded, as well as the time from unplugging until fully charged after plugging back in.

Bolt, warm 'idle' data: Data was gathered for a single 2017 Chevrolet Bolt using the Emporia Vue 2 meter. The Bolt is fully charged and then unplugged from the charger. It is then turned on and the heater set to 21°C (70°F) with some accessories that may reasonably be assumed to be used by one waiting in an idling car - generally the radio is on and the headlights are left in automatic mode, for 2 to 4 hours. It is then turned off and plugged back into the charger and the kWh to recharge to full is recorded.

F150 Lightning, warm 'idle' data: The Telematics trip-level data spreadsheets referenced above for two trucks used on the North Slope contained a few rows with 0 mile trip lengths. For those that had non-zero kWh use recorded, this and the start and end time of the 0 mile 'trip' recording were assumed to indicate that the truck was engaged in a warm 'idle'.

Tesla, mixed parking state data: Data from two Tesla EVs owned in Fairbanks, Alaska -- in a region of the state that regularly sees temperatures lower than -40°C -- and from two Tesla EVs in milder Anchorage were provided by the owners using the TezLab app [40]. The Tezlab app reports trip and charging data including mileage, time and duration, range data, electrical energy economy (kWh/mile), charge energy added, and temperature. Each owner provided a year's worth of driving and charging data for a Model 3 and a few months of data for a newer Model Y. The kWh used for each group of trips in between charging sessions, as recorded by the app from the vehicle telematics, is subtracted from the kWh of the following charging session. It is assumed that each charging session is to the same charge set-point. A check of the trip starting range after charging indicated this is usually a good assumption, although there are some exceptions. State of Charge of the battery is not in the data fields provided by the participants from their app, so we could not explicitly choose data that satisfies this requirement. The kWh remaining after this subtraction is assumed to be parked energy use - i.e. energy used by the vehicle for battery or cabin heating (i.e. warm 'idle') while the vehicle is parked and not engaged in a trip that records data. This data was not used in the linear fits for energy use in the three parked states as the data does not allow identification and separation of these states, instead it is plotted in Figure 5 to show broad agreement with the trends of the datasets that do allow parked state identification.

Tesla, warm 'idle' data: Tezlab trip (but not charging) data for the four Teslas described above and three other vehicles (the seven Teslas from Figure 2) were subsequently provided for the next year. This dataset contained a new field, total kWh used, so that for 0 mile trips, a warm idling energy use could be explicitly analyzed.

All of this data is plotted in Figure 5, and the linear fits to the data are used in the model of energy use with temperature for the calculator.

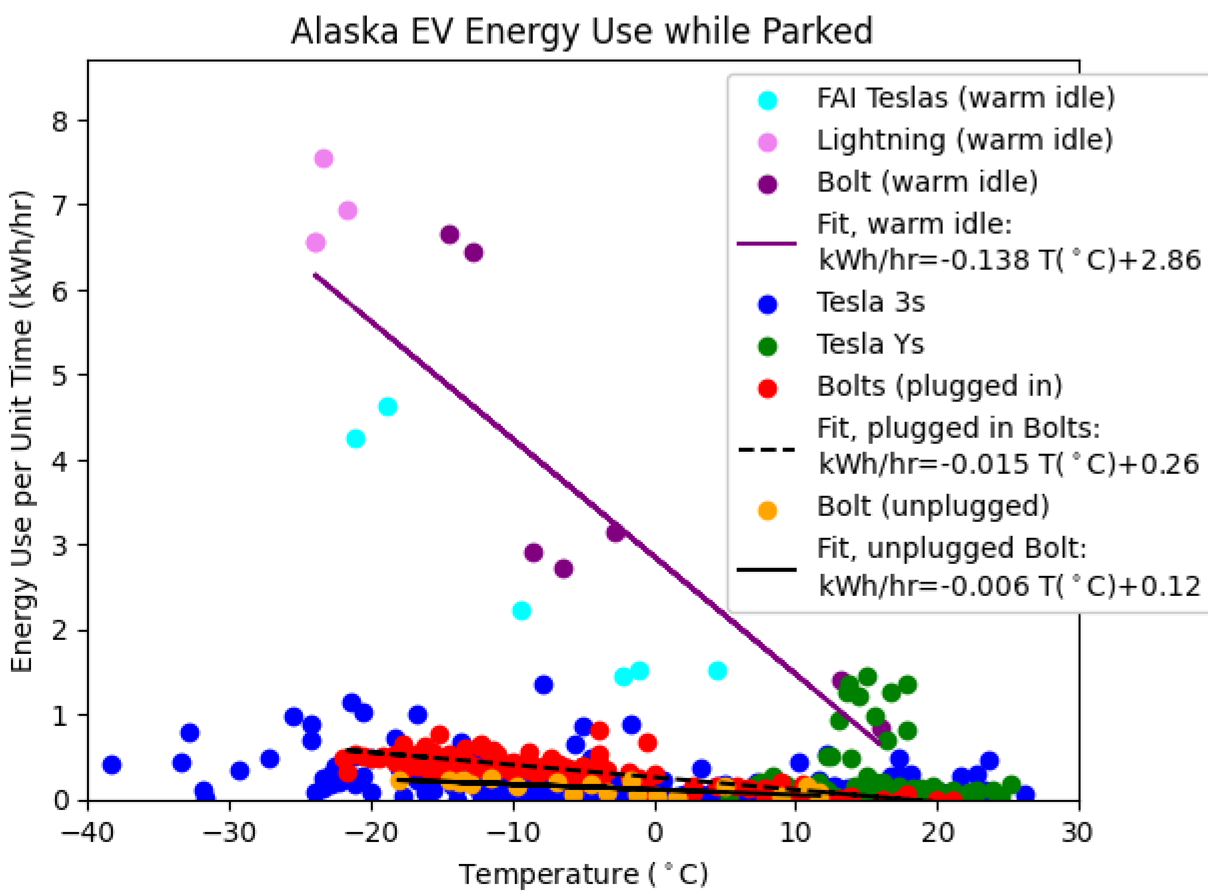

Figure 5 - Parked energy use data with fits for 3 parked states: warm idle, parked while plugged into an active charging station and parked while unplugged. Because the methodology of the Tesla data does not allow the separation of non-idling parked data from warm idling, the fits are to the other data, with the Tesla data showing broad agreement with a combination of the trends seen in the differentiated data from the other vehicles.

2.2 Calculator methodology:

Using the data and analysis performed above, a model of energy use vs. temperature and use case was developed in Python using the pandas library [41]. Along with existing databases [42, 43] related to community climate data, utility electricity rates, and emissions factors, this model forms the engine of a calculator to estimate the yearly charging costs and power plant emissions for an EV and compare them to an ICE vehicle. This tool was first made publicly available in 2020 using Streamlit [44] to provide a public web-based interface to the source code located in a publicly accessible github repository [13], and has been continuously refined with new data and user feedback.

The calculator is intended to be user-friendly, accessible, and transparent, thereby empowering users to explore different scenarios, such as varying driving distances and utility rates. During two sets of in-person public meetings and interviews in the rural Alaska communities of Kotzebue, Galena and Bethel (see Figure 1 for locations) in the spring and fall of 2022 we presented and received feedback on this calculator. We asked specifically whether the outputs were useful and what other information people would want to help with making decisions. Participants in these community meetings (n = 20) and other local partners also gave feedback on the accuracy of the results given their experience with ICE vehicles and provided feedback on and ideas to improve the ease of use, relevance, and usefulness. In this way, the communities contributed to the calculator design. Specifically, necessary user inputs were limited to four items: community, vehicle type, daily driving mileage, and price of gas (Figure 6). More advanced inputs can be controlled by the user, but are not necessary for a basic analysis and are only accessible after checking a box, in order to provide a clean interface. Outputs were modified to add a monthly plot of energy use for the electric vehicle (Figure 7). Rural residents often receive a different effective rate for power use above a certain total (currently 750 kWh/month for participating utilities) under a program called Power Cost Equalization (PCE) [45], and knowing the possible impact to monthly power consumption is very valuable for decision making. Community contributors also stressed the importance of including trucks and large SUVs in the analysis, as these vehicles are strongly preferred by many for their ability to handle rough roads and haul large loads and boats. Other feedback that has not yet been incorporated in the public calculator, but is being built into the underlying model is to allow a seasonally varying driving profile, and to include off road vehicles such as ATVs and snowmobiles.

As part of the basic inputs, users choose a community to investigate from a drop down menu. Based on the community chosen, corresponding files that contain hourly temperature data in the form of a Typical Meteorological Year and utility price and emissivity data are loaded [42, 43]. Then users select between a vehicle choice of car or truck and input their average daily miles and the price of gas. Selecting car or truck sets the following default values, which can be adjusted under the advanced inputs:

'Car': default energy use per mile of EV is 0.28 kWh (rating for a 2017 Chevy Bolt [30]), default miles per gallon for an ICE comparison is 27 mpg.

'Truck': default energy use per mile of EV is 0.5 kWh, which is the approximate rating for a variety of 2023 Ford F150 Lightning models [30], default miles per gallon for an ICE comparison is 20 mpg based on a 2023 gasoline-fueled Ford 150.

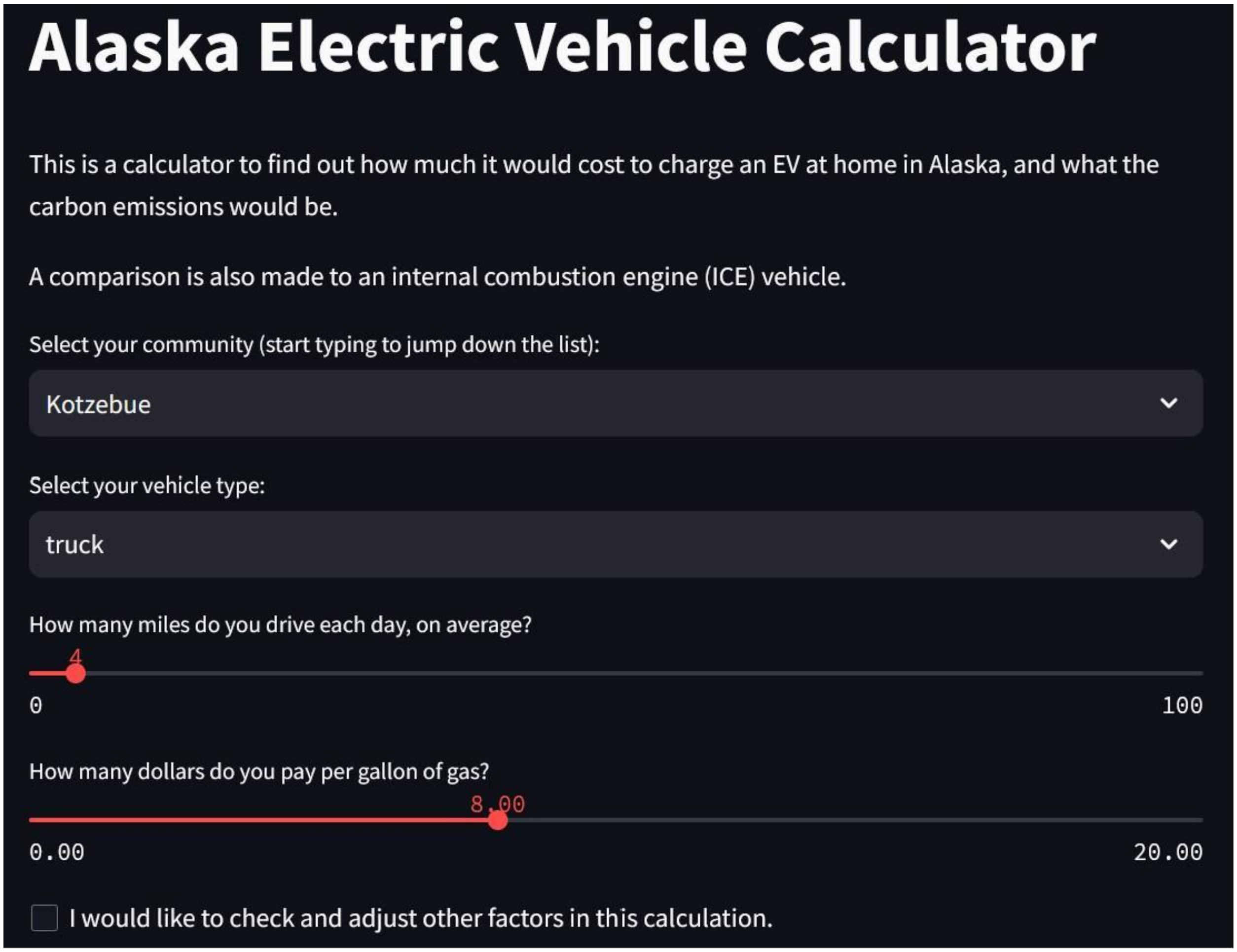

Figure 6. Screenshot of calculator showing basic inputs

If advanced inputs are selected (by the user checking a box that says “I would like to check and adjust other factors in this calculation”) the following items can be entered or adjusted from defaults:

- Weekend average daily mileage (default is to set this the same as weekday mileage)
- Park in garage (default no), and if so, the temperature setting of the garage
- Rated kwh/mile of the vehicle (defaults as above)
- Electric rates (default is the full residential rate from the utility database [43], the state’s PCE-adjusted rates are also loaded and presented to users so that they can chose to use them)
- CO_2 emissions per kWh (default to value in the utility database)
- Miles per Gallon (MPG) of comparison gas vehicle (defaults as above)
- The existence of solar Photovoltaics (PV) to offset emissions (default no), and if so, the installed size in kW
- Use of an engine block heater (default no), if so how many hours it is plugged in and used for on cold days
- Minutes of warm idle on a cold day (default 5)

A driving profile is compiled by assuming half of daily miles are driven at 8:30 am and half at 3:30 pm, at an average speed of 30 mph. Then an idling profile is created by first attributing time spent idling to the time in between the morning and evening commute, and then attributing it to the time before the morning commute then after the evening commute. The remaining time in the day is attributed to a 'parked' state. It is currently assumed that the vehicle is always unplugged when parked. While this is not true, the data gathered to date shows that the amount of time spent actively plugged into a charging station is much less than the time not actively plugged in for most drivers.

The calculator next assigns energy use throughout the day based on the relationships from Section 2 for the three states: driving, warm idle, and parked. The temperature at which a car is parked is assumed to be the ambient temperature, unless the 'garage' box is checked. In that case, it is adjusted to be the garage temperature setting between evening and morning commutes (overnight), or the ambient temperature, whichever is higher.

The total charging cost and emissions amount for a year is found from multiplying the total energy use in kWh by the utility rate and the utility emissions per kWh. For a comparison with an ICE vehicle, the fuel efficiency of the ICE vehicle is also taken to be temperature dependent [46]. For simplicity, this effect is modeled to be linear below 25°C (77°F), with 20% lower fuel efficiency at -7°C (20°F) than at 25°C. Gas use at idle is assumed to be 0.2 gallons per hour for cars, double that for trucks [47]. Note that there are fundamental differences in the assumptions for the EV vs the ICE idle. Based on the fit to data (Figure 2), the EV idling energy use does not depend on vehicle type, but does depend on temperature, which makes sense as the energy to heat the cabin will depend on the temperature differential to maintain and the size and insulation of the heated space, which is not so different between a car and pickup cab. However, the idling energy of the ICE is assumed to not be temperature dependent, but to depend on the vehicle type, as pickup trucks generally have a bigger engine and the heater in the ICE is just using waste heat from the idling engine. The assumption is made that idling is only used when the ambient temperature is below 19°C (66°F). Electricity use for ICE block heaters are also accounted for by multiplying the wattage by the hours of use for any day where the average temperature is less than -20°F (approximately -7°C), a commonly recommended temperature to use block heaters [48].

Cost of fueling the gas vehicle is taken as a sum of the amount of fuel for driving and idling multiplied by the cost of fuel and added to the cost of the electricity for block heating. Greenhouse gas emissions are calculated as 8.887 kg of CO_2 per gallon of gas burned [49] plus those due to power plant emissions for the electricity used to power the block heater.

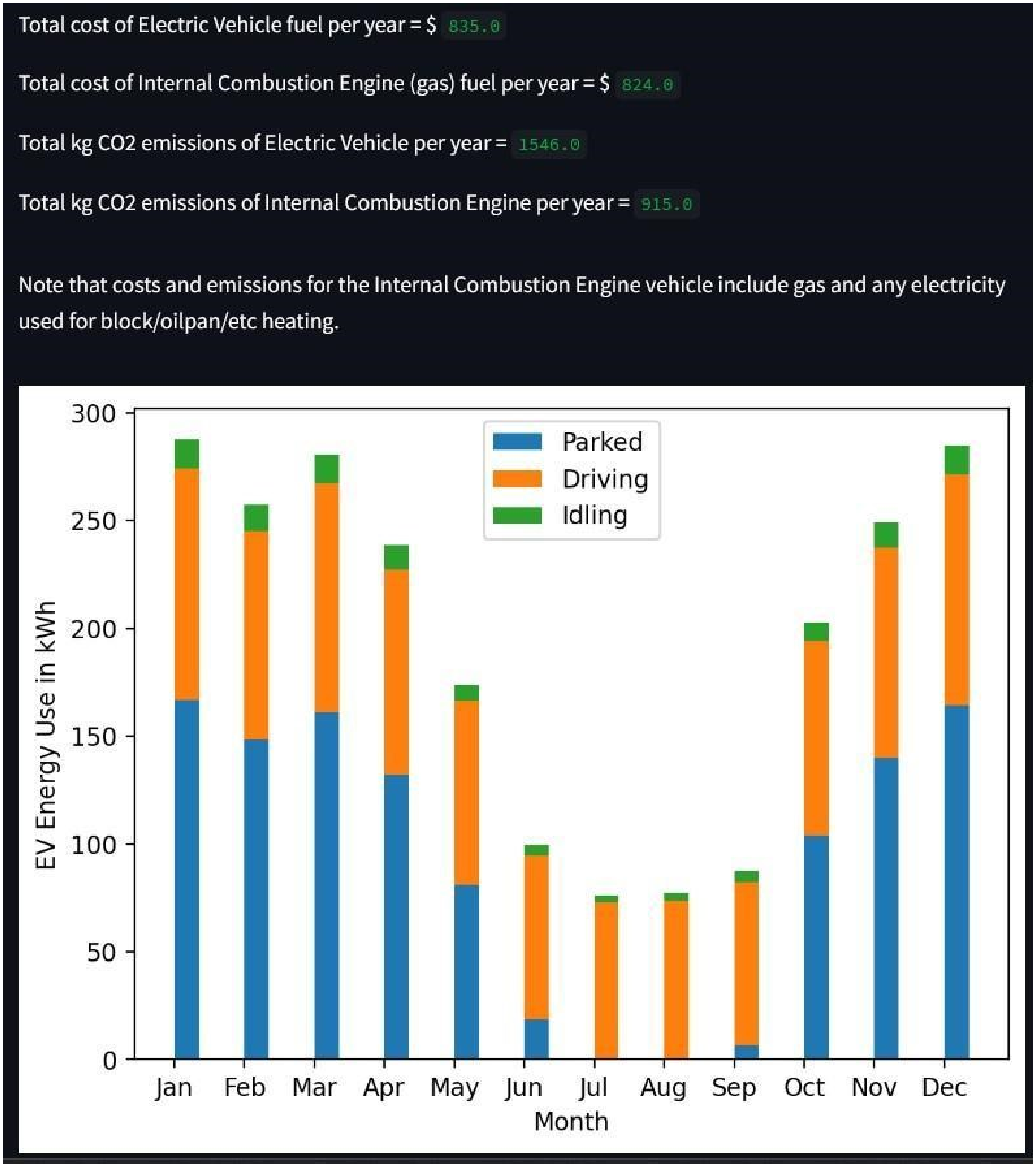

Figure 7 - Screenshot of calculator showing sample outputs. Note, while CO_2 emission comparisons are typical for low daily mileage vehicles in extremely cold regions with diesel power generation, they are by no means universal, with high daily mileage vehicles showing a large reduction in CO_2 and cost of fueling for the EV compared to gas counterparts.

2.3 Sample Output and Verification

Juneau Tesla

Over two years of data were provided by a 2016 Tesla Model S operated in Juneau, Alaska. The data was provided from the TeslaFi app [50] and is composed of extensive one-second level data while the car is in use with many fields covering driving and charging. This data was not used in any of the model-building above, and is used here boiled down to a very basic form as a broad check on the calculator. The data indicates that in 2020, 9,627 miles were driven, and 3,709 kWh were added to the car, for an average efficiency of 0.39 kWh/mi, and an average driving of 26 miles/day. In 2021, the data shows 16,082 miles driven, with 6,493 kWh added, for an average efficiency of 0.40 kwh/mi and average driving of 44 miles/day. The monotonically increasing odometer reading ensures that the mileage value is accurate, however the charging data could be low if there are any gaps in the data collection. A check of the data shows that it appears to be complete after a small gap near the end of 2019.

Using the average driving distances with the location of Juneau, an EPA rated efficiency of 0.33 kwh/mi, no idling, and parking in a 10°C (50°F) garage, the calculator gives an average efficiency of 0.42 kWh/mi at both 26 and 44 miles per day of driving, showing the low contribution of parked energy use. The modeled average efficiencies are 4% to 8% higher than the data (Table 1). This could be due to model error, missing charging data, or idiosyncrasies of the specific temperature profile and driver behavior in the actual data set. In the case where the modeled average energy use per mile is 8% higher than in the data, the actual average temperature was warmer than the model, possibly explaining some of the discrepancy.

Anchorage Bolt

A year's-worth of additional data was available from a Chevy Bolt in Anchorage used to find the model relationships in Section 2. The Bolt is parked outside and odometer readings are recorded manually, charging data is downloaded from the ChargePoint charger app. From July 2022 to July 2023, 3,628 miles were driven and 1,892 kWh used to recharge, for an average efficiency of 0.52 kWh/mi and an average of about 10 miles per day of driving. Comparisons with the calculator output are in Table 1. In this case the model is 4% high, and is not easily explained by the temperature assumptions of the model, since the actual average yearly temperature is colder than in the model. If just the modeled driving energy from the calculator is used, and parked energy is ignored, the yearly average kWh/mi is 0.37, which is 29% lower than the actual yearly average efficiency, showing the need to account for parked energy in colder regions.

Table 1. Model Validation

	Juneau Tesla 2020 - 26 mi/day		Juneau Tesla 2021 - 44 mi/day		Anchorage Bolt - 10 mi/day	
	Validation data	Model	Validation data	Model	Validation data	Model
Average kWh/mi	0.39	0.42	0.40	0.42	0.52	0.54
HDD	8185	8484	8394	8484	10,296	10,121

Average T	5.78°C	5.48°C	5.44°C	5.48°C	2.61°C	2.96°C

HDD are Heating Degree Days (base 65°F), Average T is the average temperature for the year. For the model results, these are both calculated from the hourly temperatures in the community climate database [42]. For the validation data, they are retrieved from https://akclimate.org/data/data-portal [51]

3: Discussion and Further Work

Using new crowdsourced data from EVs in Alaska, we have refined and created analytical relationships of passenger EV energy use as a function of temperature and use case. Especially novel are models of the energy use of electric passenger vehicles while parked in cold temperatures, with data down to -40°C. With these relationships, databases of Alaska community and utility information, and feedback from Alaskans, we have created a calculator to support sustainable transportation planning in the state. The accuracy of the yearly EV energy use predictions of this tool appear to be within 4-8% based on checks with data not used in the underlying analysis from two vehicles. Given the lack of existing data and models that accurately represented all energy use by EVs in very cold climates, this calculator is necessary to better understand the potential effects of the adoption of EVs in Alaska and other cold regions. The tool is open source and may be easily adapted by others in cold regions by substituting appropriate local databases for utility costs and emissions and typical yearly temperature profiles.

This calculator can be used to investigate the economic, climate, and grid impacts from EV adoption in Alaska, and in fact has been used to predict future loads in the more populous grid connected region of the state [52]. This team intends to use this tool to investigate the implications of EV adoption in rural Alaska based on new vehicle use data co-produced with our partner communities. The underlying model of energy use can be extended as needed and used for analysis of passenger EV energy use anywhere in the world.

One limitation of the calculator is the assumption of its broad applicability over a range of vehicle models. Crowd sourced data comes from a limited number of types of vehicles, in keeping with the small number and variety of EVs on the road currently in Alaska. For example, it is expected that significant changes in the size or thermal properties of the heated cabin would greatly affect the relationship of energy use vs. temperature while driving or warm ‘idling’ since a significant amount of energy goes to heating this space. Equation 2 for energy use while driving vs. temperature does not hold for electric school buses or medium duty electric trucks based on experience with data for these vehicles. It is also not expected to hold for EVs without heated cabins, like snowmobiles. Additionally, although it is expected that the heaters in an EV (battery and cabin) will have maximum outputs [8] beyond which the energy use over time will be constant at the maximum power of the heater, this is not clearly seen in the data. Collection of more data below about -25°C, especially below -40°C, should reveal this leveling off of energy use at the coldest temperatures. It is possible that the calculator overestimates parked energy use in very cold temperatures, as most of our parked energy use data is from above -20°C. Regardless, a clear result from using this calculator is the large percentage of total energy use of an EV that comes from conditioning the battery while the vehicle is parked in extremely cold climates at the typical low mileages and unconditioned parking places of rural Alaska drivers.

There is clearly a large amount of scatter in the data presented in Section 2. Some trips in the dataset likely start with a warm vehicle (from using the pre-warming feature on the vehicle without accounting for this energy use, from starting in a warm garage, or from starting a trip while the vehicle is still warm from a previous trip) and can be expected to use less energy at a given temperature than a cold-soaked vehicle. Longer distance trips often use less energy per mile than shorter ones when the car is started cold as the heating system uses full power until the set-point is reached, and trips with a high percentage of idle time use more energy per mile as the heater and other auxiliaries are still being used [22]. As noted previously in Section 2.1.1, driver behavior and heat settings, road conditions, tire choice, velocity and other factors play a quantifiable role in the efficiency and contribute to the spread in data. Analyzing the data for more of these factors will generally require data purposefully collected with higher resolution and more fields.

Continuing to refine the underlying model and assumptions with additional data will be important to ensure the accuracy of results as individuals and fleet owners look to evaluate the financial and climate effects of switching from ICE vehicles to EVs. More data is needed to better pin down the energy use requirements, especially in parked and idling modes, for a larger variety of EVs in temperatures below -20°C, and to investigate the effects of trip length and conditioned parking in heated garages. Data gathered under controlled conditions can be used to check the relationships arrived at from less controlled, crowd-sourced data.

Feedback from users in Alaska has led to simplification of the inputs of the calculator over time, pulling more information from existing databases and requiring a minimum of required user inputs to obtain a reasonable result. Users would like to see more vehicle types including snowmobiles, the ability to enter seasonal use patterns, and additional simplifications on entering information on vehicles to compare in future iterations of the tool.

As useful as a complete model of energy use given a variety of factors is, there is a tradeoff between ease of use and accuracy in the calculator based on the model. Gathering more crowdsourced data, even at the most basic level of total yearly miles driven and kWh of energy for charging, will allow better verification and show where additional work is needed to make results accurate enough, given the inputs. This is especially needed in colder regions of Alaska to verify the accuracy of modeled results in these areas where there is understandable hesitancy to adopt EVs. Further discussion with users can help determine where more or less inputs could make the calculator more user-friendly and/or helpful to decision makers. Different users may benefit from alternative versions of the tool that differ in complexity of inputs and accuracy of results.

Acknowledgements

Thanks to Alan Mitchell of Analysis North for pointing out to us his publicly available Alaska community and utility data and code to access and use them. Thanks to Christie Haupert, Tobias Schwoerer, and Steve Colt for project support and editing. Thanks to Conocophillips for sharing EV data from trucks used on the North Slope of Alaska. A special thanks to members of the communities of Kotzebue, Bethel and Galena, Alaska for your feedback on this project and the EV Calculator.

Declaration of generative AI and AI-assisted technologies in the writing process
During the preparation of this work the corresponding author used OpenAI's ChatGPT-3.5 in order to generate a first draft of an introduction. After using this tool, the authors reviewed and edited the content extensively and take full responsibility for the content of the publication.

References

1. J. Lindgren, P. D. Lund, Effect of extreme temperatures on battery charging and performance of electric vehicles, Journal of Power Sources, Volume 328, 2016, Pages 37-45, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2016.07.038.
2. P. R. Tete, M. M. Gupta, S. S. Joshi, Developments in battery thermal management systems for electric vehicles: A technical review, Journal of Energy Storage, Volume 35, 2021, 102255, ISSN 2352-152X, https://doi.org/10.1016/j.est.2021.102255.
3. M. M. Wilber, E. Whitney, T. Leach, C. Pike. Cold Weather Issues for Electric Vehicles (EVs) in Alaska, Anchorage, AK: Alaska Center for Energy & Power, 2021.
4. M.M. Wilber, C. Pike., T. Leach, M. Kitt, G. Dawei, Z.H. Kao, J. Suh, ACEP EV Map, 2020, [Online]. Available at: https://public.tableau.com/profile/michelle1506#!/vizhome/ACEPEVMAP_16061795177860/Home [Accessed Mar. 16, 2022].
5. T. Yuksel, K. Michalek, Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States, Environmental Science & Technology, Volume 49(6), 2015, Pages 3974-3980, https://doi.org/10.1021/es505621s
6. G. P. Holdmann, R. W. Wies, J. B. Vandermeer, Renewable Energy Integration in Alaska's Remote Islanded Microgrids: Economic Drivers, Technical Strategies, Technological Niche Development, and Policy Implications, in Proceedings of the IEEE, Volume 107(9), 2019, Pages 1820-1837, doi: 10.1109/JPROC.2019.2932755.
7. E. Rivelli, What is Average Mileage per Year?, 2023, [Online]. Available at: https://www.caranddriver.com/auto-loans/a32880477/average-mileage-per-year/ [Accessed Oct. 31, 2023].
8. Å. L. Sørensen, B. Ludvigsen, I. Andresen, Grid-connected cabin preheating of Electric Vehicles in cold climates – A non-flexible share of the EV energy use, Applied Energy, Volume 341, 2023, 121054, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2023.121054.
9. USDOE, Emissions from Electric Vehicles, n.d., [Online]. Available at: https://afdc.energy.gov/vehicles/electric_emissions.html [Accessed Oct. 31, 2023].

10. USDOE, Vehicle Cost Calculator Assumptions and Methodology, n.d., [Online]. Available at: https://afdc.energy.gov/calc/cost_calculator_methodology.html [Accessed Oct. 31, 2023].
11. Chugach Electric Association, Electric Vehicle Fuel and Carbon Savings Calculator, n.d. [Online]. Available at: https://evcalculator.chugachelectric.com [Accessed Oct. 31, 2023].
12. M.M.Wilber, Alaska Electric Vehicle Calculator, n.d. [Online]. Available at: https://share.streamlit.io/mmwilber/ak_ev_calculators/main/EV_Emissions.py [Accessed Oct. 31, 2023].
13. M.M. Wilber, AK_EV_calculators, 2023, GitHub repository, [Online]. Available at: https://github.com/acep-uaf/AK_EV_calculators [Accessed Apr. 5, 2024].
14. M.M. Wilber, E. Whitney, C. Haupert, A Global Daily Solar Photovoltaic Load Coverage Factor Map for Passenger Electric Vehicles, In Proceedings of the 2022 IEEE PES/IAS PowerAfrica, 2022, Pages 1–4, https://doi.org/10.1109/PowerAfrica53997.2022.99 60405364.
15. J. Neubauer, E. Wood, Thru-life impacts of driver aggression, climate, cabin thermal management, and battery thermal management on battery electric vehicle utility, Journal of Power Sources, Volume 259, 2014, Pages 262-275, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2014.02.083.
16. W. Li, P. Stanula, P. Egede, S. Kara, C. Herrmann, Determining the Main Factors Influencing the Energy Consumption of Electric Vehicles in the Usage Phase, Procedia CIRP, Volume 48, 2016, Pages 352-357, ISSN 2212-8271, https://doi.org/10.1016/j.procir.2016.03.014.
17. K. Liu, T. Yamamoto, T. Morikawa, Impact of road gradient on energy consumption of electric vehicles, Transportation Research Part D: Transport and Environment, Volume 54, 2017, Pages 74-81, ISSN 1361-9209, https://doi.org/10.1016/j.trd.2017.05.005.
18. X. Qi, G. Wu, K. Boriboonsomsin, M. J. Barth, Data-driven decomposition analysis and estimation of link-level electric vehicle energy consumption under real-world traffic conditions, Transportation Research Part D: Transport and Environment, Volume 64, 2018, Pages 36-52, ISSN 1361-9209, https://doi.org/10.1016/j.trd.2017.08.008.
19. A. Donkers, D. Yang, M. Viktorović, Influence of driving style, infrastructure, weather and traffic on electric vehicle performance, Transportation Research Part D: Transport and Environment, Volume 88, 2020, 102569, ISSN 1361-9209, https://doi.org/10.1016/j.trd.2020.102569.
20. J. Zhang, Z. Wang, P. Liu, Zh. Zhang, Energy consumption analysis and prediction of electric vehicles based on real-world driving data, Applied Energy, Volume 275, 2020, 115408, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2020.115408.
21. G. Aifadopoulou, T. Jonas, T. Wilde, C. D. Hunter, G. A. Macht, The Impact of Road Types on the Energy Consumption of Electric Vehicles, Journal of Advanced Transportation, Volume 2022, 2022, 1436385, ISSN 0197-6729, https://doi.org/10.1155/2022/1436385
22. Y. Al-Wreikat, C. Serrano, J. R. Sodré, Effects of ambient temperature and trip characteristics on the energy consumption of an electric vehicle, Energy, Volume 238, Part C, 2022, 122028, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2021.122028.

23. J. Wang, K. Liu, T. Yamamoto, T. Morikawa, Improving Estimation Accuracy for Electric Vehicle Energy Consumption Considering the Effects of Ambient Temperature, Energy Procedia, Volume 105, 2017, Pages 2904-2909, ISSN 1876-6102, https://doi.org/10.1016/j.egypro.2017.03.655.
24. X. Hao, H. Wang, Z. Lin, M. Ouyang, Seasonal effects on electric vehicle energy consumption and driving range: A case study on personal, taxi, and ridesharing vehicles, Journal of Cleaner Production, Volume 249, 2020, 119403, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2019.119403.
25. J. R. M. Delos Reyes., R. V. Parsons, and R. Hoemsen. Winter happens: the effect of ambient temperature on the travel range of electric vehicles, IEEE Transactions on Vehicular Technology, Volume 65(6), 2016, Page 4016, 2016, doi: 10.1109/TVT.2016.2544178.
26. American Automobile Association, AAA electric vehicle range testing, NewsRoom.AAA.com, 2019 Available at: https://www.aaa.com/AAA/common/AAR/files/AAA-Electric-Vehicle-Range-Testing-Report.pdf
27. F. Yang, Y. Xie,Y. Deng, C. Yuan, Predictive modeling of battery degradation and greenhouse gas emissions from U.S. state-level electric vehicle operation, Nature Communications, Volume 9(1), 2018, Page 1, doi: 10.1038/s41467-018-04826-0.
28. P. Olsen, Buying an electric car for a cold climate? Double down on range, consumerreports.org, 2019, [Online]. Available at: https://www.consumerreports.org/hybrids-evs/buying-an-electric-car-for-a-cold-climate-double-down-on-range/. [Accessed Mar. 16, 2022].
29. C. Argue, To what degree does temperature impact EV range? Geotab.com, 2020. [Online]. Available at: https://www.geotab.com/blog/ev-range [Accessed Mar. 16, 2022].
30. USDOE and EPA, www.fueleconomy.gov, 2023, [Online]. Available at: https://www.fueleconomy.gov [Accessed Oct. 31 2023].
31. C. Argue, Digging deeper into how temperature and speed impact EV range. Geotab.com, 2023. [Online]. Available at: https://www.geotab.com/blog/ev-range-impact-of-speed-and-temperature/ [Accessed Apr. 1, 2024].
32. Energetics, EV WATTS National Analysis, Fleet Vehicle Report: National. 2023. Available at: https://www.energetics.com/evwatts/reports/EVWatts_National_2023.pdf.
33. N. J. Goodall, E. Robartes, Feasibility of Battery Electric Pickup Trucks in a State Department of Transportation Fleet. Transportation Research Record, 2023 https://doi.org/10.1177/03611981231172501
34. T. Deutschen, S. Gasser, M. Schaller, J. Siehr, Modeling the self-discharge by voltage decay of a NMC/graphite lithium-ion cell, Journal of Energy Storage, Volume 19, 2018, Pages 113-119, ISSN 2352-152X, https://doi.org/10.1016/j.est.2018.07.003.
35. Chargepoint, 2023, [Online]. Available at: https://www.chargepoint.com/ [Accessed Oct. 31, 2023].
36. P3International, Kill A Watt, 2018, [Online]. Available at: https://www.p3international.com/products/p4400.html [Accessed Oct. 31, 2023].

37. Emporia, Emporia Vue: Gen 2 with 16 Sensors, 2023, [Online]. Available at: https://shop.emporiaenergy.com/products/gen-2-emporia-vue-with-16-sensors-bundle [Accessed Oct. 31, 2023].
38. NOAA, Integrated Surface Dataset (Global), n.d., [Online]. Available at: https://www.ncei.noaa.gov/access/search/data-search/global-hourly [Accessed Oct. 31, 2023].
39. Weather Underground, 2023, [Online]. Available at: https://www.wunderground.com/ [Accessed Oct. 31, 2023].
40. TezLab, TezLab - Pioneering the EV lifestyle, 2022, [Online]. Available at: https://tezlabapp.com [Accessed Oct. 31, 2023].
41. W. McKinney, Data structures for statistical computing in python, In Proceedings of the 9th Python in Science Conference, Volume 445, 2010, Pages 51–56.
42. A. Mitchell, Alaska Energy Data Site, n.d., [Online]. Available at: http://ak-energy-data.analysisnorth.com [Accessed Oct. 31, 2023].
43. A. Mitchell, n.d. [Online]. Available at: https://raw.githubusercontent.com/alanmitchell/akwlib-export/main/data/v01/utility.csv [Accessed Oct. 31, 2023].
44. Streamlit, n.d., [Online]. Available at: https://streamlit.io/. [Accessed Oct. 31, 2023].
45. Alaska Energy Authority, Power Cost Equalization Program, 2023, [Online]. Available at: https://www.akenergyauthority.org/What-We-Do/Power-Cost-Equalization [Accessed Oct. 31, 2023].
46. USDOE and EPA, Fuel Economy in Cold Weather, n.d., [Online]. Available at: https://www.fueleconomy.gov/feg/coldweather.shtml [Accessed Oct. 31, 2023].
47. B. Weber, How Much Gas is Wasted by Idling?, 2018, [Online]. Available at: https://www.chicagotribune.com/autos/sc-auto-motormouth-0308-story.html [Accessed Oct. 31, 2023].
48. MOA Health Department, Why Plug@20?, n.d., [Online]. Available at: https://www.muni.org/Departments/health/Admin/environment/AirQ/pages/whyplug20f.aspx [Accessed Oct. 31, 2023].
49. EPA, Greenhouse Gas Emissions from a Typical Passenger Vehicle, 2023, [Online]. Available at: https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle [Accessed Oct. 31, 2023].
50. TeslaFi, 2017, [Online]. Available at: https://about.teslafi.com [Accessed Oct. 31, 2023].
51. Alaska Climate Research Center, UAF, Data Portal, 2023, [Online]. Available at: https://akclimate.org/data/data-portal [Accessed Oct. 31, 2023].
52. P. Cicilio, A. Francisco, C. Morelli, M.M. Wilber, C. Pike, J. VanderMeer, S. Colt, D. Pride, N.K. Helder, Load, Electrification Adoption, and Behind-the-Meter Solar Forecasts for Alaska's Railbelt Transmission System, Energies, Volume 16, 2023, 6117, https://doi.org/10.3390/en16176117